Text as Data

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4) Validation (Model checking)$\rightsquigarrow$ weight (model) checking, replication of hand coding, face validity

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Key point: this is the same task

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- Taunting in floor statements
  $\Rightarrow$ { Partisan Taunt, Intra party taunt, Agency taunt, ... }
- Negative campaigning
  $\Rightarrow$ { Negative ad, Positive ad}

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`DICTION`

DICTION is a computer-aided text analysis program for Windows® and Mac® that uses a series of dictionaries to search a passage for five semantic features—Activity, Optimism, Certainty, Realism and Commonality—as well as thirty-five sub-features. DICTION uses predefined dictionaries and can use up to thirty custom dictionaries built with words that the user has defined, such as topical or negative words, for particular research needs.

Pre-existing word weights$\rightsquigarrow$ Dictionaries

DICTION

DICTION 7, now with *Power Mode,* can read a variety of text formats and can accept a large number of files within a single project. Projects containing over 1000 files are analyzed using *power analysis* for enhanced speed and reporting efficiency, with results automatically exported to .csv-formatted spreadsheet file.

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DICTION

On an average computer, DICTION can process over 20,000 passages in about five minutes. DICTION requires 4.9 MB of memory and 38.4 MB of hard disk space.

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> "*provides both social scientific and humanistic understandings*"
>
> —Don Waisanen, Baruch College

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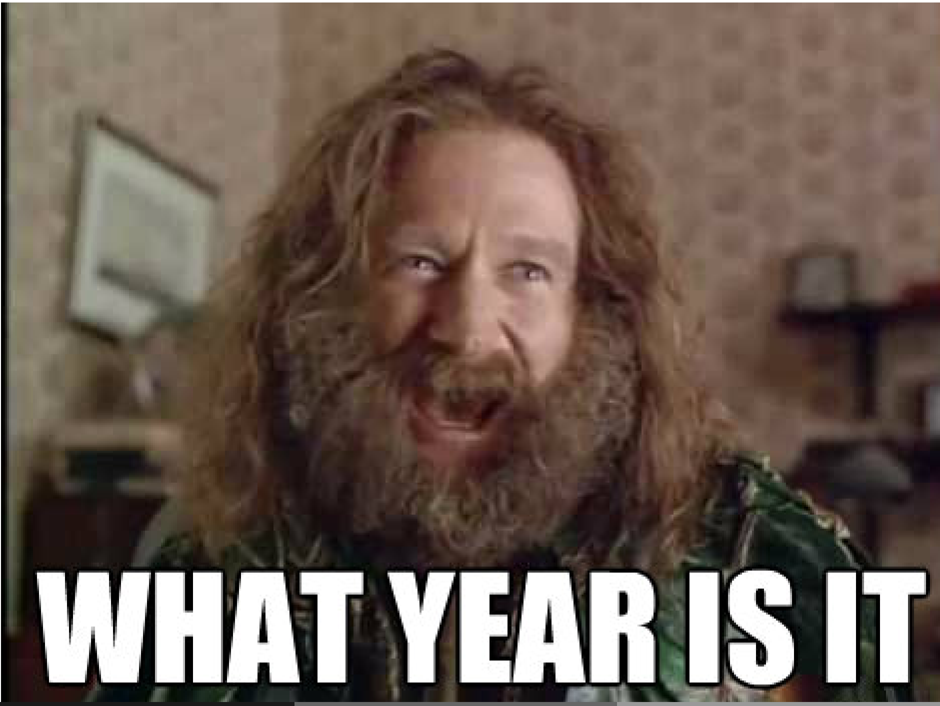
DICTION 7 for Mac (Educational) ($219.00)

This is the educational edition of DICTION Version 7 for Mac. You
purchase on the following page.


WHAT YEAR IS IT

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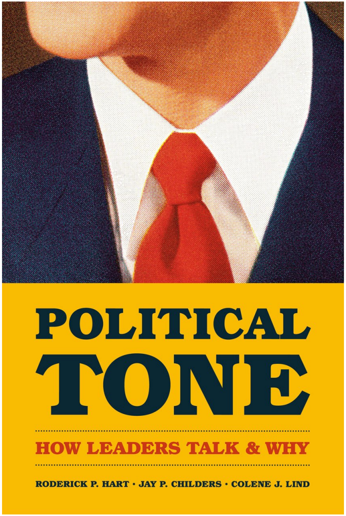
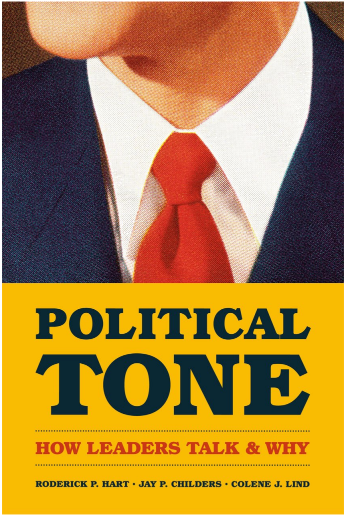

POLITICAL
TONE
HOW LEADERS TALK & WHY
RODERICK P. HART · JAY P. CHILDERS · COLENE J. LIND

DICTION



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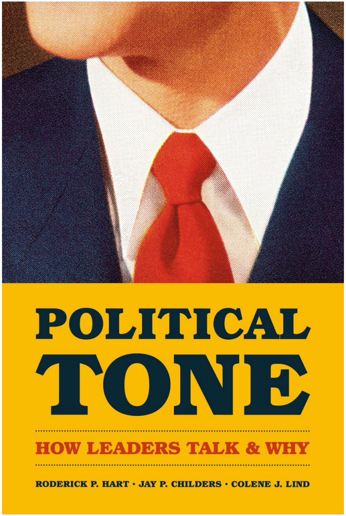

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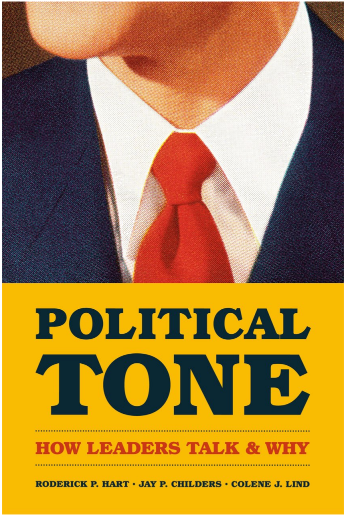

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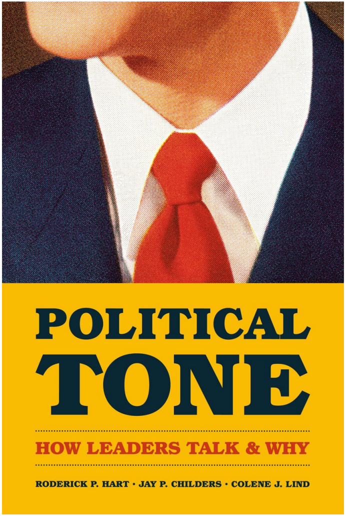

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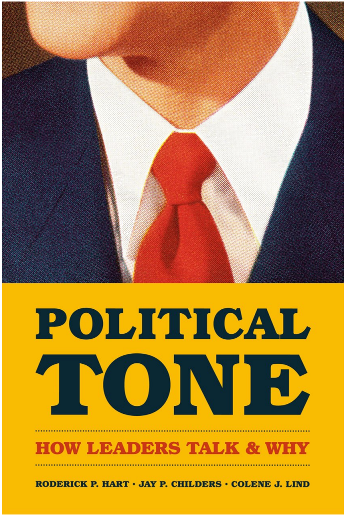

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Examine specific periods of American political history

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`Python` code and press releases

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Legislators who are more extreme $\rightsquigarrow$ less positive in press releases

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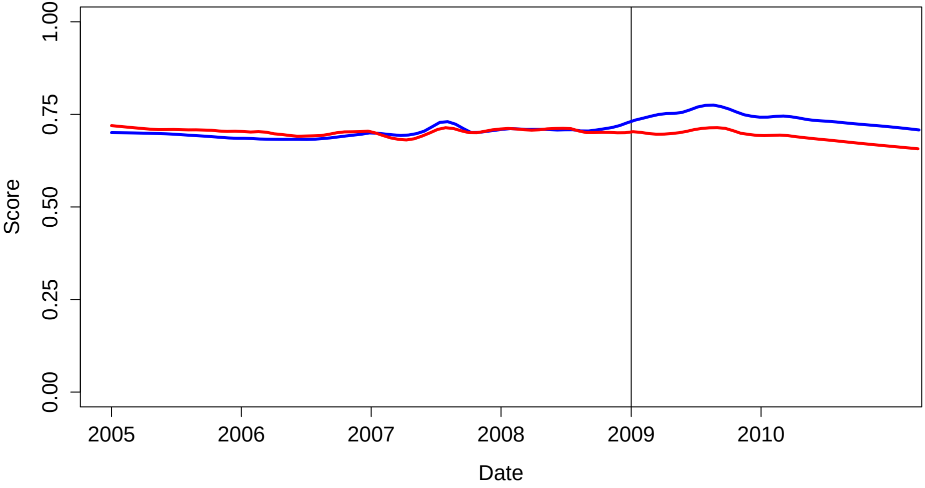

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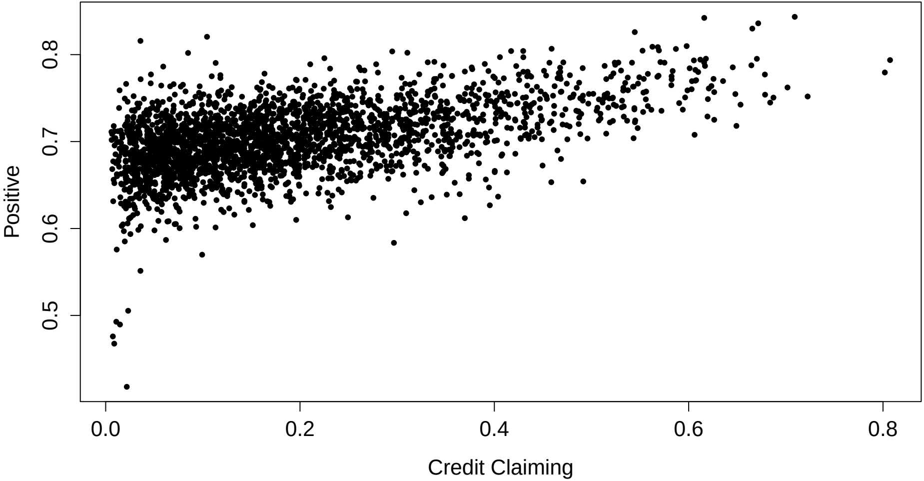

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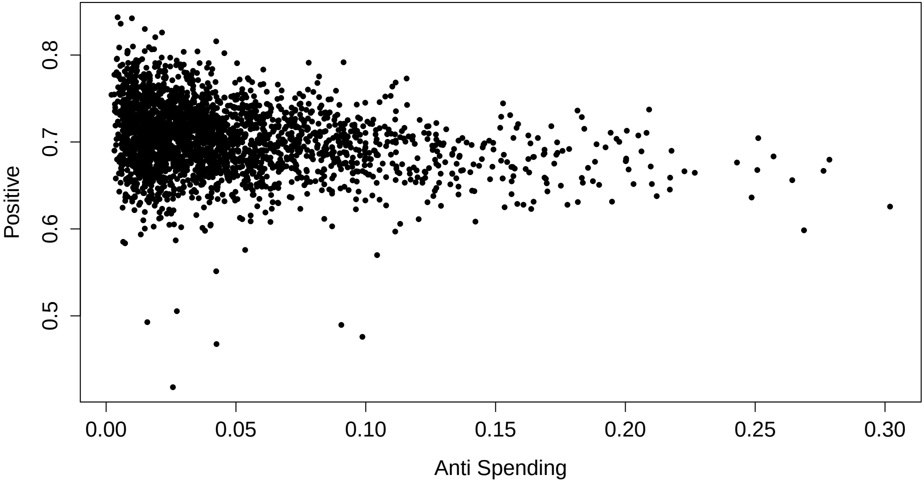

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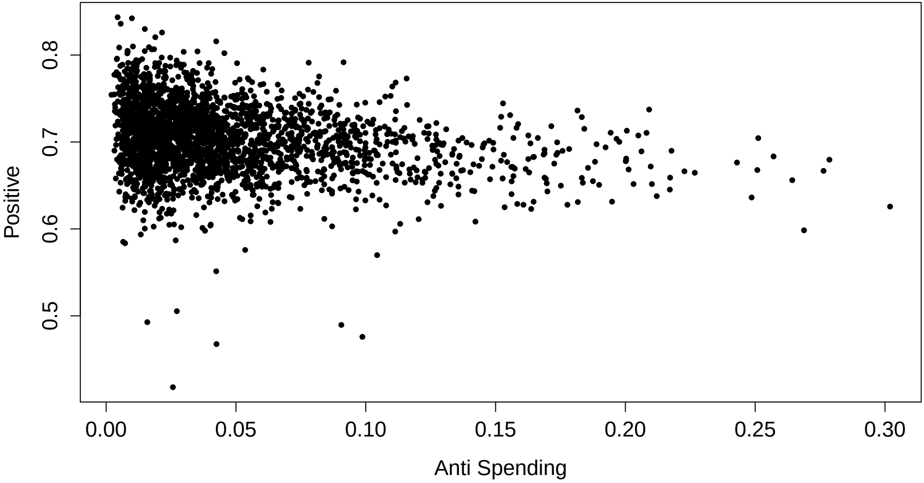

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- A procedure for training coders:
    1) Coding rules
    2) Apply to new texts
    3) Assess coder agreement (we'll discuss more in a few weeks)
    4) Using information and discussion, revise coding rules

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Measures of classification performance

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Guess	Liberal	Conservative
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Under reported for dictionary classification

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Modifiable areal unit problem in texts $\rightsquigarrow$ aggregating destroys information, conclusion may depend on level of aggregation

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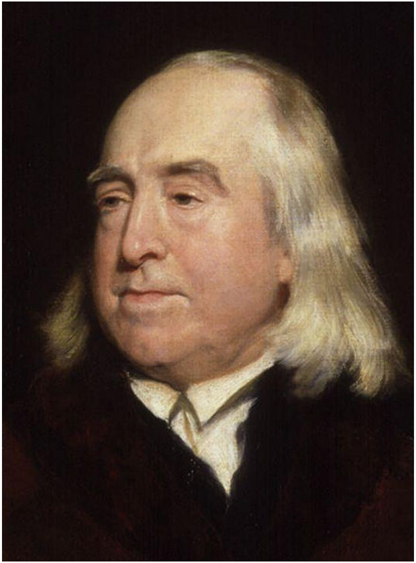
Measuring Happiness



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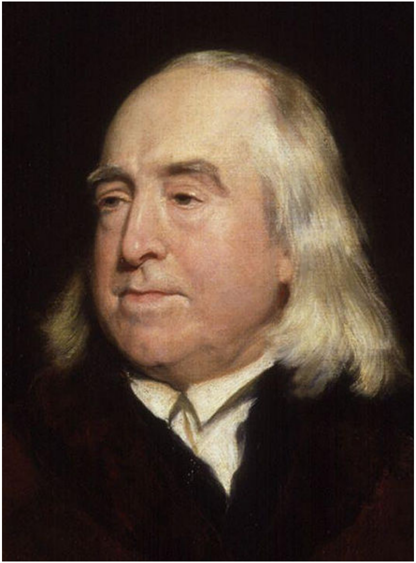

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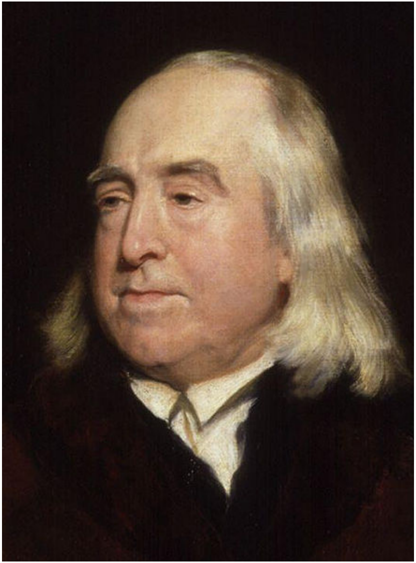

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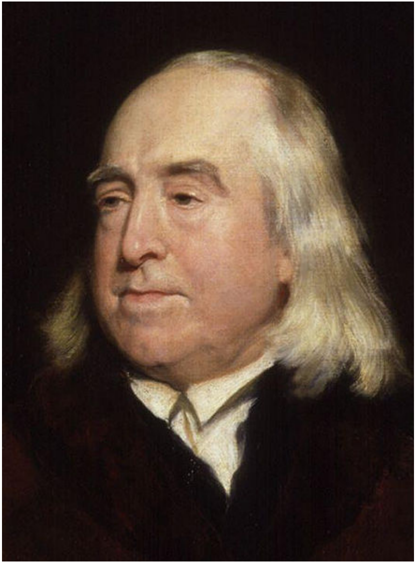

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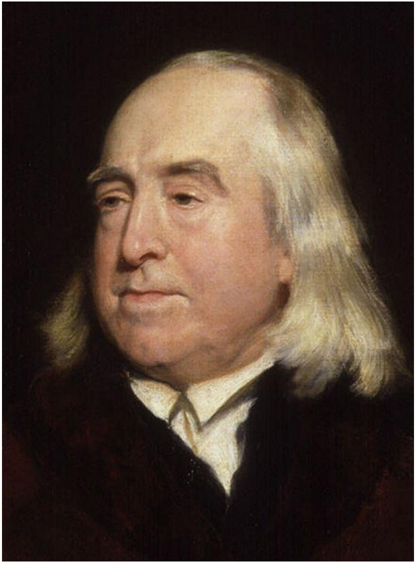

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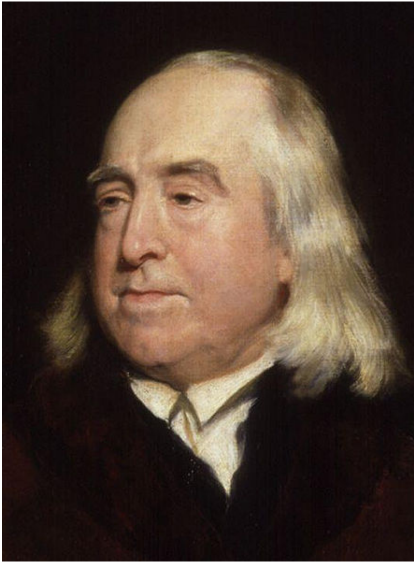
- Facebook posts? (Gross National Happiness)

Measuring Happiness



- Quantifying Happiness: How happy is society?
- How Happy is a Song?
- Blog posts?
- Facebook posts? (Gross National Happiness)

Use Dictionary Methods

Measuring Happiness

Dodds and Danforth (2009): Use a dictionary method to measure happiness

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- Affective Norms for English Words (ANEW)

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$$\text{Happiness}_i = \frac{\sum_{k=1}^{K} \theta_k X_{ik}}{\sum_{k=1}^{K} X_{ik}}$$

Lyrics for
Michael Jackson's Billie Jean

"She was more like a beauty queen
from a movie scene.
⋮
And mother always told me,
be careful who you love.
And be careful of what you do
'cause the lie becomes the truth.
Billie Jean is not my lover,
She's just a girl who claims
that I am the one.
⋮

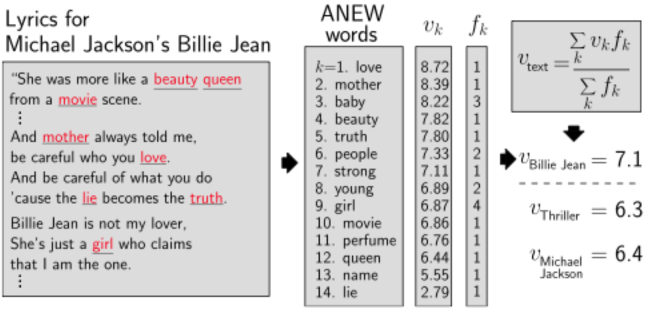
ANEW words	v_k	f_k
k=1. love	8.72	1
2. mother	8.39	1
3. baby	8.22	3
4. beauty	7.82	1
5. truth	7.80	1
6. people	7.33	2
7. strong	7.11	1
8. young	6.89	2
9. girl	6.87	4
10. movie	6.86	1
11. perfume	6.76	1
12. queen	6.44	1
13. name	5.55	1
14. lie	2.79	1

$$v_{\text{text}} = \frac{\sum_k v_k f_k}{\sum_k f_k}$$

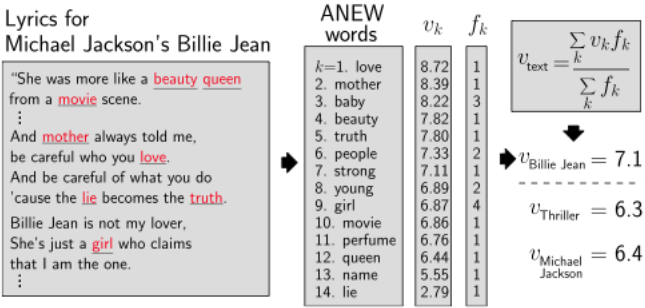
$$v_{\text{Billie Jean}} = 7.1$$

$$v_{\text{Thriller}} = 6.3$$

$$v_{\text{Michael Jackson}} = 6.4$$



Homework Hints: One approach: write a `for` loop searching for words in dictionary (caution: is dictionary stemmed?)



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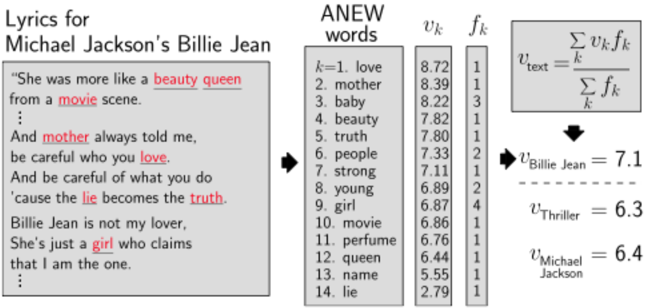
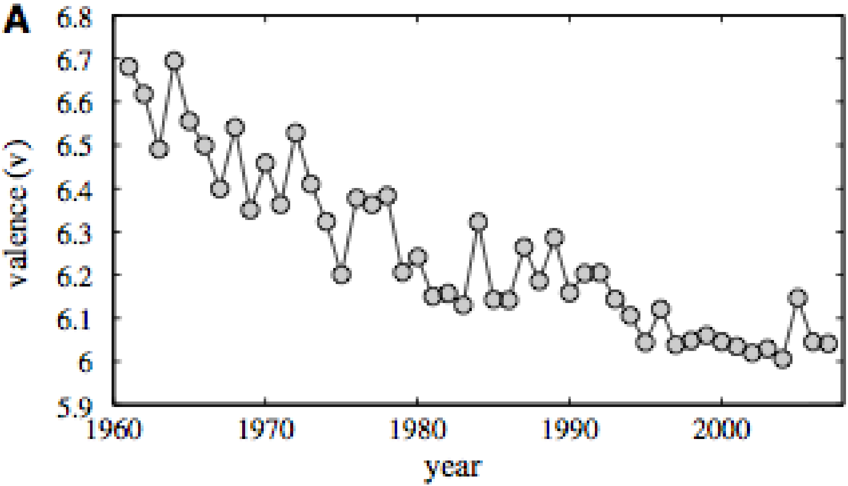
Happiest Song on Thriller?

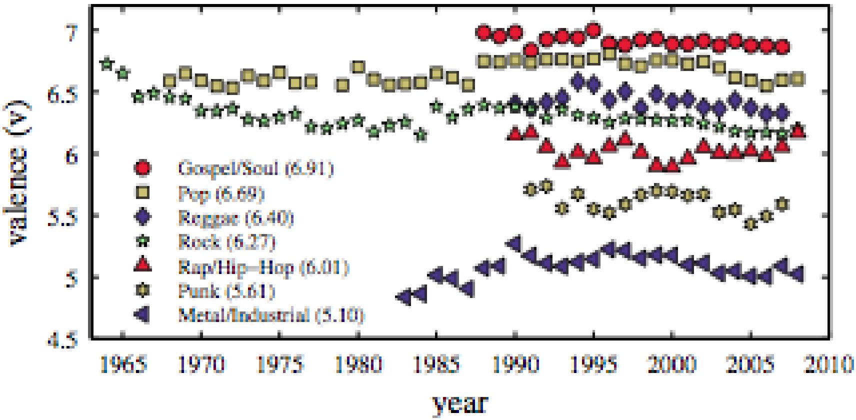


Homework Hints: One approach: write a `for` loop searching for words in dictionary (caution: is dictionary stemmed?)
Happiest Song on Thriller?
P.Y.T. (Pretty Young Thing) (This is the right answer!)

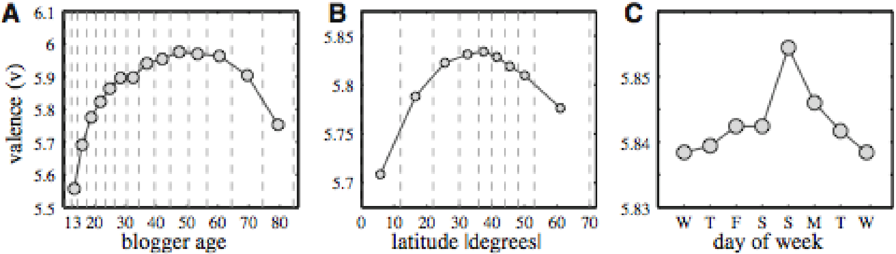
Happiness in Society



Happiness in Society



Happiness in Society



Dictionary Methods

Today: Classification via Dictionaries
Next week: Seperating Words and the Geometry of Text
Good luck on the homework!